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**ASSORTMENT VARIETY: ATTRIBUTE- VERSUS
PRODUCT-BASED**

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Assortment Variety: Attribute- versus Product-Based

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Assortment Variety: Attribute- versus Product-Based

Abstract

Retailers need to decide on the content and structure of their product assortments, and thereby on the degree of variety that they offer to their customers. This paper compares measures of assortment variety and relates them to underlying variety components. We conceptualize assortment variety from a product and an attribute perspective, compare extant measures of assortment variety, and examine the appropriateness of these measures in capturing assortment variety as perceived by consumers.

Recently, Hoch, Bradlow and Wansink (1999) introduced a general model of assortment variety based on product dissimilarities. The current study takes an alternative approach and proposes variety measures based on attributes, specifically the dispersion across attribute levels and the association between the attributes of the products in an assortment. Attribute dispersion refers to the diversity of attribute levels in an assortment (e.g. the relative proportion of red, green, blue products), while association between attributes refers to systematic links between attributes (e.g. all red products are large).

We show that product-based and attribute-based approaches to assortment variety lead to substantially different measures with different effects on consumers' perceptions of variety. A first, synthetic, data set, shows that measures of attribute dispersion, attribute association and assortment size reflect specific components of assortment variety. The product-based measure proposed by Hoch et al. is sensitive to the size of the assortment, while the attribute-based measures respond only to specific changes in the content of an assortment.

A second, consumer, data set shows that the attribute-based approach accounts best for consumers' perceptions of variety, and offers diagnostic power to retailers by explicating

variety components. Attribute-based measures of variety significantly add to the prediction of consumers' perceptions of variety, over and above the product-based variety measures, while the reverse is not the case.

In the final section we discuss how attribute-based measures can be used in assortment management, e.g. when assortments of different size are compared, when the impact of adding or dropping products on assortment variety is to be determined, and when diagnostic information about assortment variety is important.

JEL CODES: m31, c52 and c91

KEY WORDS: product assortment, variety measurement, variety perception, retailing

1. Introduction

Determining the degree of assortment variety that should be offered, has been a critical decision that retailers face since long (Elton and Mercer 1969). It is only gaining in importance with today's increasing number of product offerings (Kahn & McAlister 1997). A department store may carry over hundreds of thousands of different products, while an average supermarkets carries about 25,000 products (Ghosh 1994, p.10). In light of this development, there is a growing need for assortment and variety management in the retailing sector (Raftery 1993).

Also from a consumer perspective, assortment variety is important. The likelihood that a store carries the product that a consumer desires increases with the variety that is offered (Kahn 1998). In addition there are many situations where consumers do not have well-developed preferences and the choice process is constructive (Bettman, Luce & Payne 1998). In such cases, stores with a highly varied assortment offer more opportunity for consumers to discover their preferences and find a suitable product. Increased assortment variety can also decrease the cost of searching, by minimizing the number of store visits needed to find a desirable product (Ratchford 1982). When a store offers much variety, more information can be gathered in a single store visit. Of course, the effects of increasing variety will not all be positive, and at some point increasing variety further will lead to confusion and choice difficulty for the consumer (Kahn & McAlister 1997).

To examine the effects of assortment variety on consumer perceptions and to aid retailers assortment decisions, appropriate measures of assortment variety are required. Despite the importance of assortment decisions for retailers, research about assortment variety is of recent origin, and no single measure of assortment variety has been used consistently. Our objectives are to further explicate the concept of variety, to examine and compare proposed measures of assortment variety, and to determine how well they are able to capture the

perceived variety by consumers. To this end, we draw on the literature concerning product similarity and variety seeking behavior by consumers, the literature concerning concentration and inequality in economics, and the literature concerning statistical association. These literatures provide established and widely used measures of similarity, concentration, and association, which can be potentially useful in the context of assortment variety.

Our focus is on the variety that is due to the product assortment itself, irrespective of the format in which the products are presented. Following previous research (e.g. Hoch, Bradlow & Wansink 1999), the variety measures are applied to categorical product attributes, but extensions to continuous attributes are relatively straightforward. Our conceptualization of assortment variety departs from previous variety models based on product dissimilarities (e.g. Hoch et al. 1999), and focuses on variety measures based on attribute differences. In two data sets we show the advantage of the attribute-based approach to assortment variety. The ability of attribute-based measures to distinguish between specific components of assortment variety is another advantage which is emphasized. The results of the consumer study indicate that the attribute-based approach captures consumers' perceptions of assortment variety better than the product-based approach does, and that it offers new insights into assortment variety.

The next sections introduce assortment variety, and product- and attribute-based approaches to measure it. The measures are compared with respect to their pattern of correlations in a synthetic data set (section 4), and with respect to their ability to predict the variety as perceived by consumers (section 5). In the final section we offer suggestions for the application of the proposed variety measures in assortment management.

2. Variety offered by stores

Variety is “the quality or state of being different or diverse; the absence of uniformity, sameness, or monotony” (Pearsall 1998). There are important differences in the way assortment variety is conceptualized and measured in research. Broniarczyk, Hoyer and

McAlister (1998) focus on consumer heuristics for variety, such as the availability of the favorite brand, and the space devoted to the category. When involvement with a product category is low, consumers tend to use these heuristics rather than forming a detailed variety perception. In other situations, consumers will pay closer attention to the product assortment, and form a more detailed impression of assortment variety. These are the situations that we focus on here. Even when heuristic processing is not assumed, different measures of assortment variety have been used. For instance, some researchers argue that the sheer number of different products in an assortment captures assortment variety (Hoch & Banerji 1993; Chiang & Wilcox 1997). This measure has been criticized on the ground that it does not incorporate product dissimilarities, which are important for a good understanding of the variety concept (e.g. Pessemier 1985; Kahn & Lehmann 1991; Hoch et al. 1999). In retailing handbooks (e.g. Levy & Weitz 1998), the breadth or depth of an assortment are often taken as constituents of variety. This relates assortment variety to the number of different product groups and the number of product variants in each group. Although breadth and depth offer more detail than the sheer number of products in an assortment, they also do not take the degree of similarity between the individual products into consideration.

Hoch et al. (1999) go beyond previous work by providing a general mathematical model of assortment variety. They improve existing knowledge of the variety concept and measurement, and provide additional insight into the process of variety perception. Their model is based on the dissimilarity between products in an assortment, which we term the product-based approach. An attribute-based approach, focusing on the degree to which attribute levels are available, may complement the product-based approach and offer additional insight (Boatwright & Nunes 2000). We propose two specific attribute-based measures of assortment variety, compare these measures to the product-based measure of Hoch et al. (1999), and examine the extent to which attribute- and product-based measures

account for consumers' perceptions of assortment variety. The next section discusses the two approaches, and introduces specific variety measures that derive from them.

3. Two approaches to assess assortment variety

As products are bundles of attributes, the variety of an assortment of products can be determined based on a products-across-attributes and on an attributes-across-products examination of the assortment (Bettman, Luce & Payne 1998). To appreciate the distinction between product-based and attribute-based measures of assortment variety, consider the hypothetical product assortment in Table 1. A product-based approach would examine and compare the *products* that are offered, product-by-product. Based on the number of different attributes, neckties 1 and 2 are more similar to each other than neckties 2 and 3 are. The degree of variety in the assortment is reflected in this similarity between products: if all products differ greatly from each other, variety is high. But the variety concept has a meaning at the attribute level as well. The attribute-based approach examines and compares the *attributes* that are offered, attribute-by-attribute. For instance, if all neckties would be blue, the variety of color in the assortment would be low.

Insert Table 1 about here

Product- and attribute-based approaches differ conceptually. Note e.g. that not all entries in Table 1 can be compared. For instance, the color 'blue' can not be compared to the material 'cotton'. This implies that product-based measures, which compare products with each other by their attributes, can not be applied at the attribute level, and visa versa. The question is if product-based and attribute-based conceptualizations of assortment variety yield the same results, and, if they diverge, which approach is better able to capture consumers' perceptions of assortment variety.

3.1 Product-based approach to assortment variety

Product (dis)similarity

The product-based approach to assortment variety focuses on the (dis)similarity between products. A specific measure of product dissimilarity is the Hamming measure, which is based on a count of the number of different attributes between products (cf. Hoch et al. 1999). It ranges between 0 (when the two products are identical) and the number of attributes M (when the two products differ on all attributes), and is given by:

$$HM_{ij} = \sum_{m=1}^M d_{ijm} \quad (1)$$

where: d_{ijm} = score for attribute m ; equals 1 when attribute levels differ for products i and j , and 0 when the attribute levels for products i and j are identical
 M = total number of attributes

The Hamming measure can be determined for each pair of products in an assortment. For instance, products 1 and 2 in the assortment of Table 1 have a Hamming measure of 1 (they differ on 1 attribute). An often-used measure of product similarity is the similarity coefficient for categorical data, which computes the relative number of identical attribute levels (Everitt 1993, p. 43). When the number of attributes M is constant over the assortments, the Hamming measure and this similarity coefficient are perfectly negatively correlated. This type of measure has been applied in the marketing literature, for instance to examine similarity judgments (Bijmolt, Wedel, Pieters & DeSarbo 1998), and related (dis)similarity measures can be found in overviews of cluster analysis and other areas (e.g. Everitt 1993, Sarker 1996).

Integration of product (dis)similarities

The (dis)similarity measures compare two products to each other. An assortment consists of N products, leading to $N \cdot (N - 1)/2$ product pair (dis)similarities that need to be integrated into an overall variety measure. Two potential rules to integrate the product dissimilarities into a single measure are the mean and the sum (Tversky 1977; pp. 348-349). Variety in an

assortment can be conceptualized as the summed dissimilarities between the products in the assortment, or as the average dissimilarity. The basic model of Hoch et al. (1999), which can be extended with covariates, applies a summed measure:

$$Variety = \alpha + \sum_u \Psi(u) n_u \quad (2)$$

where: α = intercept, reflecting baseline variety perceptions
 Ψ = generalized distance function
 n_u = number of product pairs with distinction pattern u

The variety of an assortment depends on the number of product pairs with specific distinction patterns. So, the total sum of product pair dissimilarities is divided into groups of product pairs with equal dissimilarity. A distinction pattern is given by one of the possible outcomes of the Hamming measure, e.g. product pair (1-2) in Table 1 has a *HM* of 1, while both product pairs (1-3) and (2-3) have a *HM* of 2. In other words, n_1 equals the number of product pairs that differ on 1 attribute, which is 1 in the table, n_2 the number of product pairs that differ on 2 attributes, which is 2 here, and so on. When the distance function Ψ is unrestricted, a model with fitted regression weights can be estimated to account for consumers' variety perceptions. Alternatively, several models for Ψ can be considered. Hoch et al. prefer a model with diminishing returns to multiple distinctions, where $\Psi(m) = m^{1/2}$. This means that a product pair which differs on m attributes, i.e. with a Hamming measure of m , is converted into a distance of \sqrt{m} . This conversion is common in other applications as well (see e.g. Gower 1971). Hoch et al. (1999) show that the product-based measure captures a significant portion of the variance in consumers' perceptions of variety. While other product-based measures of assortment variety are feasible, we focus on this one in the sequel because of its proven validity.

3.2 Attribute-based approach to assortment variety

Our attribute-based approach to assortment variety takes a different perspective, and focuses on the presence and patterns of the attributes in an assortment. We argue that an assortment is varied when the levels of the attributes are highly dispersed, and when the association between the attributes is low. For instance, an assortment with white, blue, and green shirts will be more varied than an assortment with only white shirts. In addition, an assortment in which all white shirts have long sleeves will be less varied than an assortment in which both short sleeved white shirts and long sleeved white shirts are present. First, measures of attribute dispersion and association are introduced. Next, differences between attribute-based measures and product-based measures are examined.

Attribute dispersion

Measures of concentration as used in industrial economics are inverse measures of attribute dispersion. The more concentrated attributes are on certain levels, the less the attributes are dispersed. While various concentration measures have been proposed (Theil 1967; Jacquemin & Berry 1979; Waterson 1984; Van Trijp & Steenkamp 1990), the *Entropy* measure is predominantly used, especially in variety seeking literature (Mitchell, Kahn & Knasko 1995):

$$Entropy_m = \sum_{l=1}^L (-p_l \ln(p_l)) \quad (3) \text{ and } (4)$$

where: p_l = relative number of products with attribute level l for attribute m
 L = number of different attribute levels for attribute m

Entropy increases with increasing attribute dispersion, and ranges between 0 and a maximum value of $-\sum_{l=1}^L \left(\frac{1}{L^*}\right) \ln\left(\frac{1}{L^*}\right)$ (Van Trijp & Steenkamp 1990), where: L^* = the lesser of L and N , with L being the number of attribute levels, and N being the number of products. In most practical applications the number of attribute levels will be smaller than the number

of products.¹ The dispersion can be determined for each product attribute separately. For instance, the assortment in Table 1 contains one green product and two blue products. Therefore, the dispersion across colors is given by an *Entropy* of: $-\frac{1}{3}(\ln \frac{1}{3}) - \frac{2}{3}(\ln \frac{2}{3}) = 0.64$.

Association between attributes

A second type of attribute-based variety measures concerns the association between attributes. Whereas attribute dispersion considers the attribute levels of one particular attribute, association considers systematic links between pairs of attributes. Previous research has indicated that consumers can be sensitive to such systematic links, and may have intuitive beliefs of such links between for instance price and quality / warranty (Johnson & Levin 1985; Broniarczyk & Alba 1994). *Lambda* is a general measure of the association between nominal variables, with a simple probabilistic interpretation (Goodman & Kruskal 1954). It focuses on the mutual predictability between two variables, and results from dividing the amount of reduction in error in both variables by the amount of original error in these variables. *Lambda* lies between 0, when there is no predictive association, and 1, when there is perfect mutual predictability:

$$Lambda_{mf} = \frac{\sum_{l=1}^L \max_o(n_{lo}) + \sum_{o=1}^O \max_l(n_{lo}) - \max_o(n_{o\cdot}) - \max_l(n_{l\cdot})}{2N - \max_o(n_{o\cdot}) - \max_l(n_{l\cdot})} \quad (5)$$

where: N = number of products in the assortment

n_{lo} = the number of products with attribute levels l and o for attributes m and f , respectively

$n_{l\cdot}$ = the number of products with attribute level l for attribute m (marginal count)

$n_{o\cdot}$ = the number of products with attribute level o for attribute f (marginal count)

The assortment of Table 1 contains 2 blue cotton neckties, 0 green cotton neckties, 0 blue silk neckties, and 1 green silk necktie. Therefore, the association between color and material as given by *Lambda* is $((2+1) + (2+1) - 2 - 2) / (2*3 - 2 - 2) = 1$. Color and material have perfect predictive association. Alternative association measures have been proposed, but *Lambda* is frequently preferred for its interpretability (e.g. Bishop, Fienberg & Holland 1975;

Leach 1979). A high level of attribute association means that the variety offered by the assortment is low. To ease its interpretation in comparison with other variety measures, we use $(1 - \textit{Lambda})$ as a measure of disassociation, which increases when variety increases.

Integration of attribute-based measures

The attribute-based measures need to be integrated across the attributes to obtain a measure at the assortment level. The dispersion measures can be summed or averaged over the attributes, while the disassociation measure can be summed or averaged over the attribute pairs. In most practical implications, assortments of comparable products will be examined, and the number of attributes will be constant. Hence, using the sum or the mean has no implications for the results. In the sequel we consider averaged attribute-based measures of variety for convenience. We present the results of two data sets in which product-based and attribute-based measures are compared. In the first, synthetic data set we examine the correlation between the various measures to establish to which extent they overlap or differ from each other in a well-behaved environment. In the second, consumer, data set we examine the predictive validity of product-based and attribute-based measures for consumers' perceptions of variety.

4. Relationships between the measures of assortment variety

The product-based approach leads to a single, overall, measure of assortment variety, and it does not consider variety components and their intercorrelations. In the area of consumers' variety seeking over time, the use of multiple measures for different aspects of variety is common (e.g. Pessemier & Handelsman 1984; Meulenberg 1989; Menon & Kahn 1995). The attribute-based approach identifies two aspects of variety that theoretically differ from each other. By providing information about these variety components, the attribute-based approach may complement the product-based approach to assortment variety. But it is not obvious

whether and to what extent the product- and attribute-based variety measures overlap and capture the same variety concept, or whether they capture different aspects of assortment variety. To examine this issue we use synthetically constructed data. We investigate the pattern of correlation between the diverse measures in a well-behaved environment, across a large number of assortments.

Four product-based measures can be distinguished, based on the distance function (either $\Psi(m) = m$ or $\Psi(m) = m^{1/2}$) and on the integration rule (sum or average): (1) the sum of the Hamming measures (*SumHM*), (2) the average Hamming measure (*MeanHM*), (3) the sum of the square roots of the Hamming measures (*SumSRHM*), and (4) the average of the square roots of the Hamming measures (*MeanSRHM*). The fitted regression weights model of Hoch et al. (1999) will be used in the consumer data set, where a dependent variable is available to estimate the weights. Here, we use the preferred function by Hoch et al. (1999), the distance function $\Psi(m) = m^{1/2}$, to obtain variety measures. In addition to the four product-based measures, we consider average *Entropy* and average $(1 - \text{Lambda})$ as attribute-based measures. Finally, we consider the number of products in the assortment as a general measure of assortment variety (*Size*), since it has been used in previous assortment research, and to examine the extent to which product- and attribute-based measures capture different information than is contained in the size of the assortment.

When variety is a multidimensional construct, *SumSRHM*, the overall measure of variety, should correlate with the variety components (attribute dispersion and attribute association), and with assortment size, but only to a moderate extent. In addition, the intercorrelation of the measures of the variety components should be relatively low to support that they are separate components. If the correlation between assortment size and the product- and attribute-based measures would be very high, the unique contribution of the latter measures would be reduced.

Assortments were constructed that consisted of products with three attributes. Each attribute could have four different levels, which in total led to 64 different products. With these products, 64^N possible assortments of size N can be constructed. Assortments with 8, 12 or 16 products were considered to allow sufficient size variation. A random sample of 3000 product assortments was drawn from the population of $64^8 + 64^{12} + 64^{16} = 7.9 \cdot 10^{28}$ possible assortments, allowing for duplication of products and assortments. Of these, 1000 consisted of 8 products, 1000 of 12 products, and 1000 of 16 products.

4.1 Results

Table 2 presents the correlations between the measures, and shows clear differences in the size of the correlations. The product-based measures that employ an average as integration rule do not relate well with the other variety measures. They correlate only little with the summed product-based measures (between .04 and .07) and not at all with assortment size. In addition, the averaged product-based measures correlate negatively with $(1 - \text{Lambda})$, which measures the variety that is revealed by the disassociation between attributes.

Insert Table 2 about here

The summed product-based measures have a moderately high correlation with the attribute-based measures (between .45 and .59), but they have an almost perfect correlation with assortment size (.99). In addition *SumHM* and *SumSRHM* themselves are also almost perfectly correlated $(.9997)^2$. The near perfect correlation of the two product-based measures with assortment size is a serious concern as it suggests limited unique contribution of the product-based measures over and above the assortment size. Also, evaluating the variety of assortments with different sizes may be cumbersome with *summed* product-based measures.

Using *averaged* product-based measures instead does not alleviate this, in view of the potential problems associated with these measures³.

One might conjecture that the near perfect correlation between the product-based measures and assortment size was perhaps due to the relatively large steps in which assortment size was increased in this data set. Follow-up analyses with assortments differing less in size (8, 9 and 10) showed that this was not the case (correlation of .98 between *SumSRHM* and *Size*). The high correlation between the summed product-dissimilarities and assortment size is due to the fact that adding one additional product to an assortment of N products leads to the addition of N product pairs in the summed measure. Especially when assortment size is large, this effect may dominate changes in assortment content.

With respect to the measures of the variety components, Table 2 indicates that the two attribute-based measures, *Entropy* and $(1 - \textit{Lambda})$ have a low intercorrelation (.06), which suggests that they tap different aspects of assortment variety. Correlations with assortment size are substantial (.55 and .48), but much lower than between the summed product-based measures and size. The attribute-based approach leads to moderately correlated measures of variety components that respond to specific changes in product assortments.

But does it really matter how assortment variety is measured, i.e., which measures capture consumers' perceptions of assortment variety best? This is explored in the next section.

5. Consumers' perception of assortment variety

This consumer study compares product-based and attribute-based measures of assortment variety, and examines how well these measures capture consumers' perceptions of variety.

5.1 Method

Participants and design. Participants were 62 undergraduate students from a university in the Netherlands. Each participant made judgments about twelve product assortments, which

differed with respect to size, attribute dispersion and attribute association. The basic setup of the assortments was a 2 (assortment size: 8 versus 16) x 2 (dispersion level: low versus high) x 3 (association level: low, medium and high) within-subjects design, to ensure that the assortments differed to a large extent.

Stimuli. Stimuli were comparable to those used by Hoch et al (1999).⁴ Non-existing products were used for the following reasons: (1) to provide a clear example of variety perceptions, without the potentially distorting effects of prior experiences, product preferences, and expertise, and (2) to allow comparison with previous research in this area, in particular with the Hoch et al. (1999) study. Using non-existing products ensures that participants of the study are not influenced by characteristics of the product category, or by their preferences, and make variety judgements based on all the products in an assortment.

The products were characterized by three attributes, with four different levels each:

- color (red, blue, yellow, green)
- shape (square, rectangle, circle, triangle)
- name (CAM, NUX, ZOL, VIK)

In total, 64 different products can be constructed from these attributes. Each assortment contained 8 or 16 products arrayed in two or four rows with four products each. The products were presented in an organized manner, to simulate a store shelf. Products were grouped by color and within color by form, following attribute importances. Presentation format was not manipulated, since we focus on content variety only. Since similar products and attributes were in close proximity, both the product-based and the attribute-based approach are relatively easy to use for the participants.

Procedure. The study was administered on personal computers using the program Authorware (Macromedia 1997). Participants were told that the purpose of the experiment was to investigate variety perceptions. The instruction mentioned a visit to a number (not specified) of different stores, and asked participants to answer questions about assortments of

an imaginary product called 'jinko'. The instruction explained that jinkos are comparable to other product categories, where products can differ on characteristics such as name, taste, size, color, and so on. Next, participants were shown all possible types of jinkos (64), which each appeared sequentially on the computer screen for 2 seconds. After training, participants were exposed to the assortments of jinkos in random order, and were asked the following questions (each with a ten point scale, with endpoints labeled 'not at all' and 'very much'):

- Does this assortment of jinkos offer a lot of variety?
- Does this store offer a monotonous assortment of jinkos?
- Does this store offer a diverse assortment of jinkos?

Cronbach's alpha, calculated across participants for each of the assortments, lies between .70 and .89, with an average of .77. Scores across the three items were averaged after reverse coding the negatively worded item. The overall mean across participants and assortments was 5.78. Participants proceeded at a self-determined pace, and product assortments remained visible during the task. Participants took about 20 minutes to complete the study, and received the equivalent of \$5 for their participation.

5.2 Product assortments

An overview of the product assortments and variety measures is presented in Table 3, and examples of the computer screen are provided in Appendix 1. The specific attribute levels (e.g. whether the first product is red, blue, yellow or green) were randomized. Assortments consisted of either 8 or 16 products. Attributes were either equally dispersed (all levels occurred in equal proportions), or two of the levels dominated the other two (in proportion 3 to 1). When all attributes had perfect association, the assortment contained replicas. Attribute association was manipulated in three levels: (1) low association, (2) high association, which introduced replicas, and (3) partial association, in which all but one assortment (number 12) had no replicas. In the third case, color and form were perfectly associated, while brand name was not associated with color or form. By this manipulation, the effects of attribute

association and the introduction of replicas can be assessed independently. The last column of Table 3 provides the mean variety perception of each assortment.

Insert Table 3 about here

5.3 Results

The main question of the study is whether the product-based and attribute-based measures differ in the extent to which they capture consumers' perceptions of variety. Multilevel linear regression models (Bryk & Raudenbush 1992; Goldstein 1995), using MLwiN (Rasbash, Healy, Browne & Cameron 1998), were estimated to account for the fact that each participant in the study judged multiple assortments. The models predict variety perceptions, while accounting for individual differences, by treating assortments as nested within participants. The following regression was estimated:

$$PVAR_{ak} = \mathbf{b}_0 + \mathbf{b}_1 n_{1a} + \mathbf{b}_2 n_{2a} + \mathbf{b}_3 n_{3a} + \mathbf{b}_4 Size_{ak} + \mathbf{b}_5 Disp_{ak} + \mathbf{b}_6 Assoc_{ak} + u_{0k} + e_{0ak} \quad (6)$$

where: n_u = number of product pairs with u different attributes
 $PVAR_{ak}$ = variety of assortment a as perceived by individual k
 $Size_{ak}$ = size of assortment a for individual k
 $Disp_{ak}$ = attribute dispersion of assortment a for individual k (*Entropy*)
 $Assoc_{ak}$ = attribute association of assortment a for individual k ($1 - \text{Lambda}$)
 β_0 = overall mean
 β_q = regression weights
 u_{0k} = participant level residual
 e_{0ak} = assortment level residual

Restricted versions of the model were compared through nested model testing, to determine the incremental contribution of attribute-based variety measures, product-based variety measures, and assortment size. The general model of Hoch et al. with fitted regression weights was used as comparison, since this should provide a stronger test than the *SumSRHM* variety measure, which is based on a predefined distance function Ψ . Table 4 provides an overview of model estimations.

Insert Table 4 about here

Product-based variety model. Model 1 in Table 4 is the fitted regression weights model of Hoch et al. (1999), and it accounts for 43.1 % of the variance in perceived assortment variety. The negative coefficient for n_3 is unexpected and differs from the (positive) coefficients reported by Hoch et al. The explanation lies in the impact of assortment size. If we consider only assortments of equal sizes, the coefficients become 0.49, 0.73 and 0.76 (n_1 , n_2 , and n_3) for assortments with 8 products, and 0.13, 0.18 and 0.19 for assortments with 16 products, which is more in line with previous findings. When assortment size increases, the number of product pairs increases even more rapidly. This will affect the product-based measures. By including *Size* (model 3) we adjust for the inflation of the measures due to differences in assortment size, hence its negative coefficient of -1.99 .⁵

Assortment size. Model 2 is the model with only *Size* as an explanatory variable. By itself, *Size* accounts for only 3.4 percent of the total variance in perceived variety. Assortment size does not appear to be a good overall proxy for assortment variety in this study.

Product-based and assortment size variety model. Model 3 contains both the product-based measures and assortment size. Despite the large correlation between the two in the previous, synthetic, data-set, the results show that the product-based measures when empirically weighted in the regression analysis capture a sizeable portion of variance in consumers' variety perceptions over and above the variance accounted for by assortment size. Each of the three product-based measures, n_1 to n_3 , is significant at $p < .001$, and hence the difference between model 3 and 2 is significant as well ($p < .001$).

Attribute-based variety model. Model 4 is the attribute-based model of assortment variety. The results are as expected: both an increase in attribute dispersion (coefficient =

8.437; t -ratio = 10.155) and an increase in attribute disassociation (coefficient = 4.715; t -ratio = 32.575) lead to higher perceived variety. Model 4 is also the best overall model.

The model comparisons in the lower part of Table 4 show that the attribute-based variety model can not be significantly improved by adding the product-based measures or even assortment size (comparison of models 4 and 6: $L^2 = 4.1$, $df = 4$, $p = .393$). But, the reverse is not the case: attribute-based measures account for consumers' variety perceptions in addition to the product-based measures (model 3 versus 6: $L^2 = 189.7$, $df = 2$, $p < .001$). Hence, when the focus is on predicting consumers' perception of variety the two attribute-based measures of assortment variety suffice.

6. Conclusion

We compared measures of assortment variety, both conceptually and in two data sets. The attribute- and product-based approaches reflect basic conceptualizations of assortment variety: assortment variety as a single dimension based on the sum of product dissimilarities, and assortment variety as a multi-dimensional construct based on the dispersion and association of product attributes. The synthetic data set showed that product-based measures of assortment variety are highly influenced by assortment size, and appear to offer little additional insights beyond the size of an assortment. Given the large size of typical store assortments, which greatly exceeds the sizes used in both this paper and previously published data sets, our results indicate that care is needed when using the summed product-based measures to compare assortments of even marginally different sizes. The consumer data set showed that this potential problem is alleviated by using empirical weights in the analysis. With these weights, the product-based measures significantly add to the prediction of consumers' variety perceptions over and above the sheer size of an assortment. In spite of this additional contribution, the attribute-based measures were capable of significantly adding to the product-based measures.

The two proposed attribute-based measures of assortment variety capture specific components of variety: attribute dispersion (*Entropy*), and disassociation between attributes ($1 - \textit{Lambda}$). The two measures are only moderately correlated with assortment size. The number of products in an assortment (*Size*) did not significantly add to a model with attribute-based measures in this research. But since it is possible to change assortment size without changing the dispersion across attribute levels and the association between attributes, future research might include assortment size, in addition to the attribute-based measures to examine assortment variety.

Despite its limitations, the product-based approach has important merits as well. By carefully examining the pattern of product dissimilarities, it offers opportunities to find influential products, as Hoch et al. (1999) show. It is good to note that the attribute-based approach can accomplish this as well for specific attributes. Attributes with a low level of dispersion may require additional attention. Low dispersion may be a sign that specific attribute levels are not well represented in the products contained in the assortment. A particularly low level of disassociation between two specific attributes is an indication that some of the possible combinations between the attributes are not well represented by the products in the assortment.

Implications for retailers and manufacturers. The attribute-based approach to assortment variety is useful in retail management for several reasons. First, it is important for retailers to apply measures of assortment variety that have a systematic empirical relationship with the variety perceptions of consumers in which the final interests lies. Since the perception process itself was not examined, we can not be sure that consumers formed their variety perceptions through the attributes. However, the literature on information search shows that consumers emphasize attribute information when they are exposed to product sets through information boards (Bettman et al. 1998). Also intuitively, it is not unlikely that consumers

focus on the attributes when they form a variety judgment. Imagine walking into a clothing store to discover the latest fashion. One of the first things that may stand out is the color of the clothes, and maybe the cut or material: looking around one easily forms a perception of variety based on these attributes, and perhaps not by comparing every single clothing item with the other items. Comparing each of the available products may be beyond the cognitive capacity of most consumers.

Second, the attribute-based approach allows retailers to examine if the variety in an assortment is high because it has many different attribute levels, or because it has a clever combination of far less attribute levels. An analysis into why, e.g., low disassociation between product attributes exists, may provide opportunities for introducing combinations of attribute levels that increase disassociation and thereby increase perceived variety. A more detailed analysis of attributes with low levels of dispersion can point out attribute levels that occur in relatively low numbers. This can offer directions for category management.

Third, an attribute-based approach can lead to different managerial decisions than a product-based approach, as the latter tend to assign a systematically higher variety to larger assortments, while attribute-based measures are less prone to do so. Retailers seeking to increase the variety offered by a product assortment will find that an overall measure, such as *SumSRHM*, increases most when products are added to the assortment. By using our measures of variety components, alternative routes to increase assortment variety may open up.

Insights from the store assortment literature can also be applied to manufacturers who market a range of products. The development of an optimal product line and the management of a product portfolio are challenges for manufacturers (Zenor 1994), and an attribute-based approach can support this.

Limitations and future research. There are several important limitations of our research and several points of discussion. First, assortment size and attribute dispersion were only presented to the participants at two different levels, which is not a natural situation. We do not believe, however, that the limited range explains the advantage of attribute-based measures over product-based measures. Rather, the analyses of the synthetic data indicated that the product-based approach is sensitive to assortment size. Manipulating assortment size further in the consumer study by including larger assortments would likely strengthen our results, as assortment size would dominate even more. In addition, we conjecture that consumers' perception of large assortments will be based even more on the attributes, as suggested by information processing research (Stone & Schkade 1991). We expect that larger differences in assortment size will favor the attribute-based measures even more, a conjecture which future research may examine.

Second, the synthetic data set showed that the attribute-based measures were correlated, albeit not very high. This correlation may complicate the distinction between the variety components and the identification of their influence. Still, the consumer study showed that distinguishing the variety components offers insights into assortments that can not be obtained otherwise.

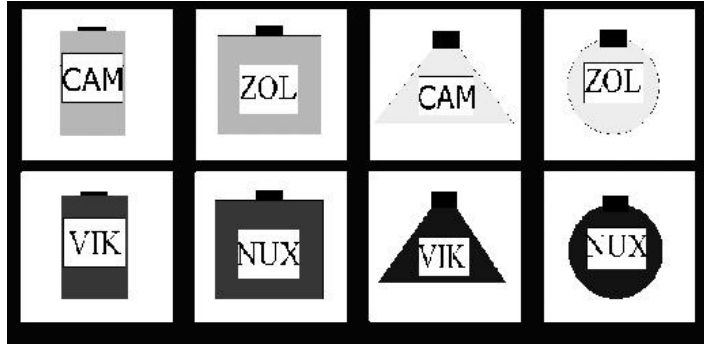
Although we closely followed the procedures in previous research, an additional point of discussion is our use of laboratory settings and hypothetical products in a relatively high involvement context. Follow-up research in real market situations is desirable. The perception of variety and assortment evaluation in situations where motivation and/or ability to process all assortment information is low is needed. In real life consumers have prior knowledge, product preferences, and experience with different store formats. All these could potentially influence the evaluation process, but were not considered in this research.

A specific avenue for future research is the effect of differences in experience between consumers. For instance, novice consumers may easily infer variety from the size of an assortment, while expert consumers may incorporate attribute dispersion and attribute association in their variety judgment. Future research could also investigate consumer search behavior in different types of assortments. Depending on the content and variety of an assortment, search processing may be different. For instance, when stores carry large assortments, the costs of information acquisition for an additional product is lower on average, since less stores need to be visited. Larger assortments also enable more direct product comparisons. On the other hand, if attribute dispersion is low, while association between attributes is high, a store offers very similar products, and the marginal gains from searching additional products in such as store are low. The costs and benefits of information acquisition in a store depend on the structure and content of the product assortment that is offered. As a consequence, differences in the information acquisition process and outcomes may result.

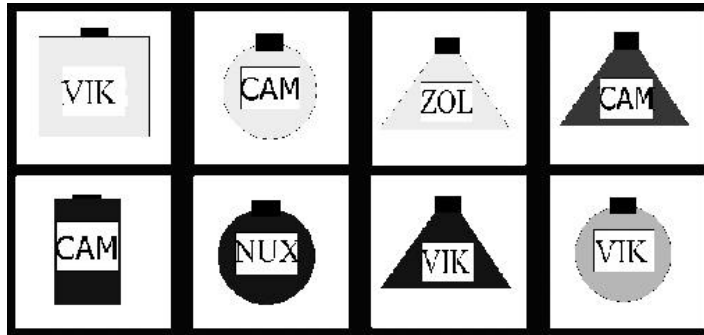
Another avenue for future research is consumers' preference for specific assortments. One question is, e.g., in which situations consumers prefer assortments with high or low variety. When variety is high, consumers may perceive a higher likelihood that the assortment contains a desired product, but the potential confusion resulting from such an assortment can also increase. The assortment that is preferred may depend on the specific search and purchase goals (e.g. under time pressure, the ease with which a product can be chosen from an assortment may be more important), and consumer characteristics (e.g. experts may be better able to deal with high-variety assortments). It seems worthwhile to link the attribute-based conceptualization of variety to consumers' preference for different assortments.

Appendix 1 Examples of product assortments used in the empirical study

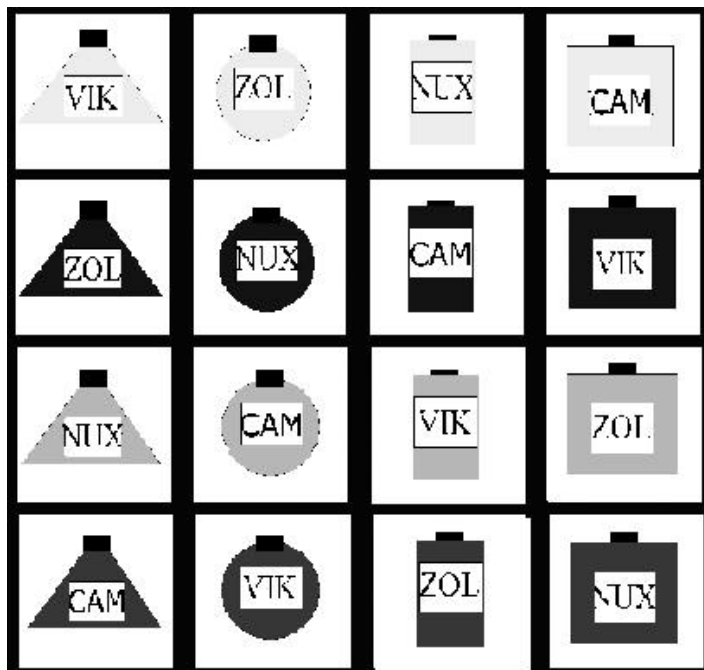
Assortment 2:



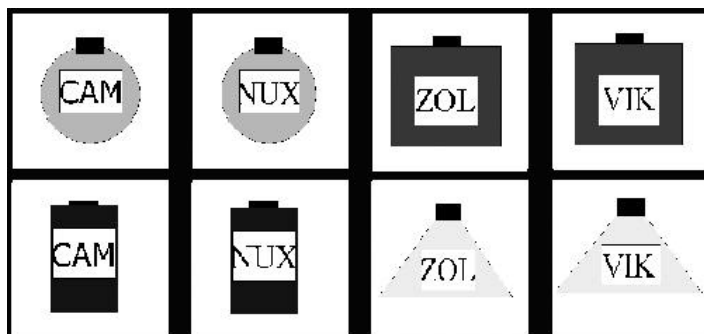
Assortment 4:



Assortment 6:



Assortment 9:



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Endnotes

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- ¹ *Relative Entropy* (*Entropy* divided by $Entropy_{max}$) can also be used as a measure of attribute dispersion. In the two data sets in this paper, $Entropy_{max}$ is constant, and results for *Entropy* and *Relative Entropy* are identical.
- ² When no distance conversion is applied to a product-based measure, as with *SumHM*, the resulting measure does not respond to changes in the association between attributes (cf. Hoch et al. 1999, p.534). The measure responds to the dispersion of the attribute levels, but not to permutations of the levels within an attribute. Using the square root as a distance function, resulting in *MeanSRHM* or *SumSRHM*, ensures that the measure increases when attribute association decreases, which is desirable.
- ³ Note that Table 2 shows a negative correlation between averaged product-based measures and the measure for disassociation between attributes. In addition, averaged product-based measures can decrease when products are added to an assortment, which is undesirable. For instance, consider an assortment with a blue cotton shirt and a green woolen shirt, giving an average Hamming measure of 2 for this assortment. Adding a blue woolen shirt would increase assortment variety, but it decreases the average Hamming to $(1+1+2)/3 = 1.33$.
- ⁴ We thank the authors for access to the stimuli used in their studies. Two of the original product names were changed, as one refers to a meaningful object and the other is a slang word in Dutch.
- ⁵ Based on this finding, one may argue that the product-based measures can be adjusted by dividing each of the measures n_1 to n_3 by *Size*. However, this does not improve their predictive power. A model of $n_1/size$, $n_2/size$, and $n_3/size$ (-2 LL = 3006.2; #par = 6) still has a negative coefficient for the latter variable, and adding *Size* significantly improves it ($L^2 = 134.3$, $p < .005$). Other results are similar to Table 6 as well.

Table 1 Content of a hypothetical product assortment of neckties

Attributes	Necktie 1	Necktie 2	Necktie 3
Color	Blue	Blue	Green
Material	Cotton	Cotton	Silk
Pattern	Stripes	Dots	Dots

Table 2 Correlations between the variety measures

	<i>MeanHM</i>	<i>MeanSRHM</i>	<i>SumHM</i>	<i>SumSRHM</i>	<i>Entropy</i>	<i>(1 – Lambda)</i>
<i>MeanSRHM</i>	.97					
<i>SumHM</i>	.07	.06				
<i>SumSRHM</i>	.04	.04	1.00			
<i>Entropy</i>	.79	.77	.59	.57		
<i>(1 – Lambda)</i>	-.28	-.10	.45	.47	.06	
<i>Size</i>	.00 (n.s.)	.00 (n.s.)	.99	.99	.55	.48

n=3000; correlations higher than .06 are significant at $p < .001$

Table 3 Description of the product assortments used in the consumer study

Assortment number	Differences between product assortments			Measures of assortment variety ¹							Mean variety perception
	Number of different products	Attribute dispersion	Attribute association	<i>Size</i>	<i>Sum SRHM</i>	n_1	n_2	n_3	<i>Entropy</i>	<i>(1-Lambda)</i>	
1	4	1:1:1:1	All high	8	41.57	0	0	24	1.39	0.00	3.85
2	8	1:1:1:1	All low	8	44.68	0	12	16	1.39	0.67	7.18
3	4	1:1:3:3	All high	8	38.11	0	0	22	1.26	0.00	3.01
4	8	1:1:3:3	All low	8	42.78	0	18	10	1.26	0.80	6.51
5	4	1:1:1:1	All high	16	166.28	0	0	96	1.39	0.00	3.51
6	16	1:1:1:1	All low	16	184.96	0	72	48	1.39	1.00	8.90
7	4	1:1:3:3	All high	16	152.42	0	0	88	1.26	0.00	3.48
8	16	1:1:3:3	All low	16	176.18	12	72	36	1.26	1.00	7.46
9	8	1:1:1:1	1 high, 2 low	8	44.30	4	4	20	1.39	0.44	6.19
10	8	1:1:3:3	1 high, 2 low	8	42.20	6	6	16	1.26	0.53	5.37
11	16	1:1:1:1	1 high, 2 low	16	182.65	24	24	72	1.39	0.67	7.81
12	12	1:1:3:3	1 high, 2 low	16	171.52	28	28	60	1.26	0.67	6.06

¹ n_u provides the number of products with u different attributes, as used in Hoch et al. (1999) and in equation 2 here

Table 4 Multilevel model estimates and comparisons

Model	Coefficient	<i>t</i> -ratio	<i>p</i> -value ¹	-2LL	#par.	Variance accounted for (assortment level)
0. <i>constant</i>	5.777	53.365	<.001	3452.2	3	-
1. <i>constant</i>	5.171	33.247	<.001	3068.2	6	43.1
<i>n</i> ₁	0.043	5.695	<.001			
<i>n</i> ₂	0.052	18.755	<.001			
<i>n</i> ₃	-0.016	6.667	<.001			
2. <i>constant</i>	4.499	15.900	<.001	3428.8	4	3.4
<i>size</i>	0.107	4.864	<.001			
3. <i>constant</i>	15.908	15.191	<.001	2968.5	7	50.8
<i>n</i> ₁	0.139	11.952	<.001			
<i>n</i> ₂	0.205	13.686	<.001			
<i>n</i> ₃	0.210	9.567	<.001			
<i>size</i>	-1.991	10.360	<.001			
4. <i>constant</i>	-2.918	2.646	.010	2782.9	5	62.5
<i>entropy</i>	8.449	10.155	<.001			
(1 – <i>Lambda</i>)	4.756	32.575	<.001			
5. <i>constant</i>	-3.153	2.829	.006	2781.0	6	62.6
<i>size</i>	0.019	1.387	.171			
<i>entropy</i>	8.437	10.154	<.001			
(1 – <i>lambda</i>)	4.715	31.749	<.001			
6. <i>constant</i>	-3.780	1.024	.310	2778.8	9	62.7
<i>n</i> ₁	0.004	0.221	.826			
<i>n</i> ₂	-0.008	0.316	.753			
<i>n</i> ₃	-0.006	0.159	.874			
<i>size</i>	0.074	0.230	.819			
<i>entropy</i>	8.774	5.418	<.001			
(1 – <i>lambda</i>)	4.893	14.262	<.001			
<i>Model comparisons</i>						<i>L</i> ² df. <i>p</i> -value
1 – 3	adding size to product-based measures				99.7	1 <.001
2 – 3	adding product-based measures to size				460.3	3 <.001
2 – 5	adding attribute-based measures to size				647.8	1 <.001
4 – 5	adding size to attribute-based measures				1.9	1 .168
3 – 6	adding attribute-based measures to product-based measures & size				189.7	2 <.001
4 – 6	adding product-based measures & size to attribute-based measures				4.1	4 .393

¹ *p*-values are based on approximate standard errors provided by MLwiN